INTEGRATED SENSING FOR CIRCUIT BOARD INSERTION

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Integrated Sensing for Circuit Board Insertion

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Abstract — To automate tasks like assembly, disassembly, repair and maintenance, the issues arising from environmental uncertainties must be addressed. An integrated sensing approach which addresses uncertainties is presented for two robot systems equipped with multiple sensors. The target tasks involve the insertion of printed circuit boards into cages. Sensors are used to calibrate the robot to the workspace, locate the supply of printed circuit boards and the destination insertion slots. A fingertip lightbeam sensor is used to refine the location information to the precision required for a successful insertion. Two plausible approaches are explored to test some of the sensing concepts. One approach examines blind system sensing strategies; the other examines vision sensing in conjunction with fuzzy reasoning. A controller which is based on fuzzy logic is used to interpret the forces and torques generated by the wrist-mounted force-torque sensor during the insertion process. Experimental results confirm the validity of the modeling assumptions for the board insertion domain. These explorations represent the first steps which lead toward the development of integrated sensing skills to perform generic activities such as *insert* and *locate*.

I. INTRODUCTION

Robots are still far from the flexible automation tool they were envisioned to be. Present day robots generally operate with minimal sensing and use a control strategy based on open loop positioning [Engelberger, 1]. Thus the reproducibility of the task depends upon the repeatability of the robot motion and the experimental setup used. A reliable robotic system has to be able to accommodate uncertainties in the environment due to poor repeatability of the robot, changes in the workspace, and variations in the pose (position and orientation) and dimensions of the workpieces. For this reason feedback from the workspace is required; that is, sensors have to be used. This article reports on research aimed at the development of elemental, smart sensors to be employed for control of robotic actions. This requires the ability to integrate information of different sensing modalities, different spatial resolutions, and different geometric configurations: integrated sensing.

Integrated Sensing

Sensing can provide a snapshot of the environment. When inputs from multiple sensors are employed for real-time feedback in the control of robotic actions, the sensing must be integrated with the proper interpretation to select the appropriate responses. This requires some knowledge about the context of the activity. Thus, for this purpose, *integrated sensing* is understood to encompass all the sensing and commands which are required to accomplish a specific goal. As such, it includes the integration of information from all sources, the use of context to drive the sensing activities, the active scheduling of sensing tasks, and the maintenance of a holistic system perspective.

Relation to Previous Work

Primitive robotic activities need to be programmed for robots to perform tasks like assembly, repair, or maintenance. Some programming languages incorporate both robot motion primitives and sensory interactions. *AL* by Mujtaba and Goldman [2], *LM* by Latombe and Mazer [3], and *AML* by Taylor, Summers and Meyer [4] are examples of such languages. The part-mating issue has received considerable attention. Brooks [5] reports on fine-motion planning which involves sensor-guided motions to achieve part-mating. Dufay and Latombe [6] report on a solution to the problem of mating two parts requiring sensor-based strategies to deal with geometric uncertainties. Their strategy is to monitor assembly forces. The robot motion is carried out until a sensor-based condition is met. The motion is stopped once the condition is met, even if the desired goal is not achieved. Several approaches for controlling the robot which use forces measured from sensors on the manipulator are suggested in the literature. Cutkosky and Wright [7] present a survey of these strategies. Two of these approaches are based on compliance, one passive and the other active. Nevins *et al.* [8] describe passive compliance which uses compliant tools. Nevins *et al.* [8, 9] describes active compliance which is achieved by using servo loop compensators.

To test some of the sensing concepts, printed circuit board insertion is being investigated. Two plausible approaches are explored. One approach examines blind system sensing strategies; the other examines vision sensing in conjunction with fuzzy reasoning. These explorations represent the first steps which lead toward the development of integrated sensing skills to perform generic activities such as *insert* and *locate.* To put this into perspective, the notion of integrated sensing *specialists* is explained first. Then two insertion experiments are described. This is followed by a discussion of the use of fuzzy logic for insertion. Finally, some experimental results are presented.

II. SPECIALISTS

Specialists are part of the architecture of the real-time hierarchical knowledge-based robotic systems which have been reported by Basañez *et al.* [10], Kelley *et al.* [11-13], and Moed *et al.* [14, 15]. The specialist level consists of functional units whose purpose is to execute operational commands issued by the real-time supervisor-dispatcher level. There are three types of specialists: coordination, transformation, and observation. Coordination specialists control the activities of multiple transformation and observation specialists. Transformation specialists employ action agents to transform the state of the environment; and observation specialists employ various sensors to determine the state of the environment.

Typically, sensor-rich robotic systems have instrumented grippers, manipulators, and environments. Sensors which are available in an instrumented gripper, such as the gripper shown in Figure 1, might include a between fingertip lightbeam, finger-mounted proximity sensors, clamping force sensor, and a mechanical overload sensor. In addition, an instrumented manipulator might include a wrist-mounted force-torque sensor and active vision system mounted on the arm or in the gripper. An instrumented environment might include platform force-torque sensors, and either a binocular stereo camera system, a ranging system, or a trinocular vision sensing system. Thus, specialists are one means of integrating diverse sensing capabilities in such sensor-rich systems.

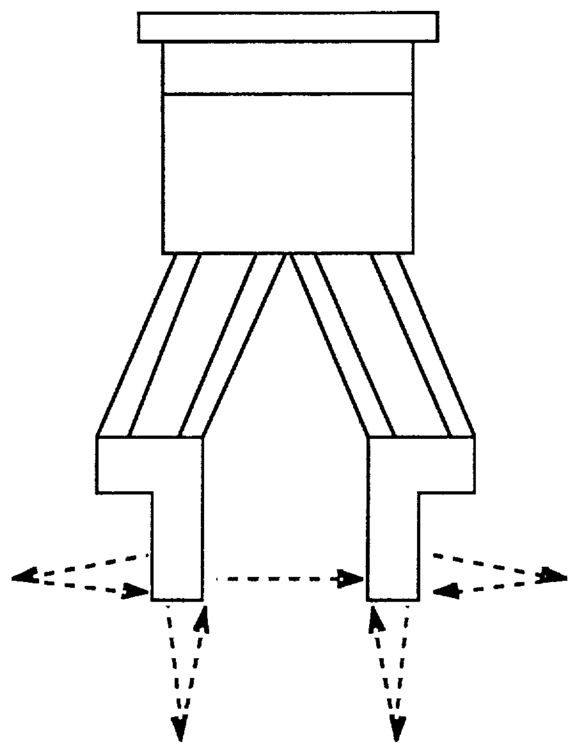

Figure 1. Instrumented gripper: fingertip light beam sensor and four proximity sensors shown.

For the board insertion experiments, two kinds of sensing coordination specialists are used: *location* and *insertion* specialists. The location specialist uses whatever sensors are available to locate a specified object to the precision required. Since it might require both observation and transformation specialists to accomplish the location task, it is an example of a coordination specialist. The insertion specialist controls insertion tasks. Hence it coordinates the sensing and insertion activities which are performed by appropriate specialists. Two versions of the location and insertion specialists are described in the next section.

III. BOARD INSERTION EXPERIMENTS

Blind Insertion

The experiment for the blind insertion of printed circuit cards uses a robot which is computer-controlled. It is equipped with a pneumatic force- and position-servoed, instrumented gripper as previously described. A 4D force-torque sensing platform (3 orthogonal forces, torque about an axis perpendicular to platform surface) is used to support the destination cage. The environment is provided with a calibration post and horizontal reference surface as shown in Figure 2. The board cages are equipped with reflective side strips for use by the infrared proximity sensors.

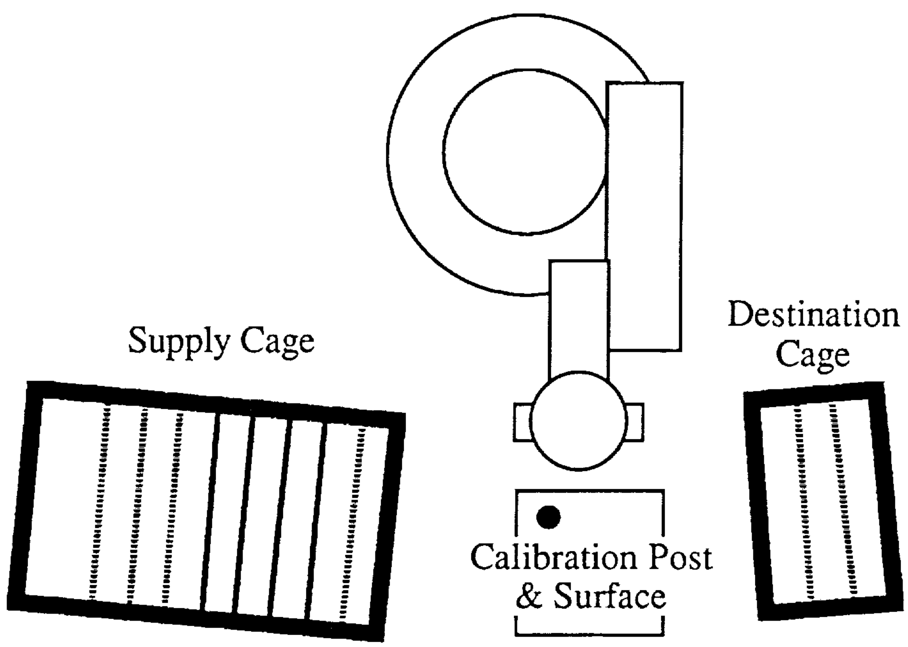

Figure 2. Layout for the blind insertion experiment. The board supply cage is on the left, the calibration post and horizontal reference surface are in the center, and the destination cage is on the right.

The blind insertion task consists of removing a board from a supply cage and inserting it into a slot in the destination cage. Uncertainty is introduced by allowing the workspace coordinate system to differ from the pose of the off-line nominal coordinate system pose by as much as 3 cm and 10 degrees. Further, the planar pose of both the supply cage and the destination cage are allowed to vary randomly in the same range. The operational phases of the blind insertion experiment are described next.

Workspace Calibration

Workspace calibration is performed by a coordination-type calibration specialist. First, downward-directed proximity sensors are used to determine the surface normal of a horizontal reference surface. The normal is found by lowering the gripper until one fingertip is at the maximum response distance above the surface. The gripper is rotated in the fingertip plane about this point on the surface until the other fingertip is at the maximum response distance. This determines the direction of the surface normal in the plane of the fingertips. The search is repeated in the plane which is perpendicular to the first fingertip plane to completely determine the direction of the surface normal in the robot coordinate system.

Next, the displacement of the coordinate origin in the plane of the reference surface is determined by means of the calibration post. The fingertip lightbeam sensor consists of an infrared LED and a photo-transistor. The calibration post is located by sweeping the nominal post area with the fingers opened to about 10 cm. The coordinates of the lightbeam interruption in two perpendicular sweep directions allow the centerline of the post to be located.

Cage Location

Initially, the location specialist locates both the supply and destination cages by means of sideward-directed proximity sensors. Thereafter, this procedure is performed only if one of the cages is replaced or systematic location errors are encountered. The reflective strips on the side of the cages are detected by a sideward-directed proximity sensor as the gripper moves towards the nominal center location of the strip. The maximum response distance as the gripper scans the length of the strip is used to determine the orientation of the cage. The ends of the strip determine the position of the cage in workspace coordinates.

Removal and Insertion

Cards are removed from the supply cage by moving along the centerline above the cage until the gripper is positioned over the nominal position of a board. The gripper is then lowered until the fingertip lightbeam sensor is interrupted by the top of the board. The gripper descends an additional amount to obtain enough finger contact area to reliably grasp the board. The board is grasped and withdrawn vertically to clear the supply cage. It is then moved above the target slot in the destination cage.

The insertion specialist uses a platform torque-force sensor to monitor the direction of the insertion vector in the board guides until the board is properly seated in the socket. For this experiment, the guides capture the board with sufficient control to permit the board to drop down the guide to the socket. The board is re-grasped and seated in the socket. Thus, only the Z-force is monitored for such insertions. (Since the platform sensor provides only limited error recovery capability, the board is removed and put into a recycle box if the fingertip lightbeam sensor detects that it does not drop when released in the guide.)

Vision-Aided Insertion

The experimental set up for the vision-aided insertion task consists of a robot, a host computer, three basic sensors, and assembly fixtures [16-18]. The first sensor is a 3D vision system comprised of two CCD cameras and four lights suspended above the robot workcell as shown in Figure 3. The cameras are calibrated with respect to the robot's coordinate system using a method

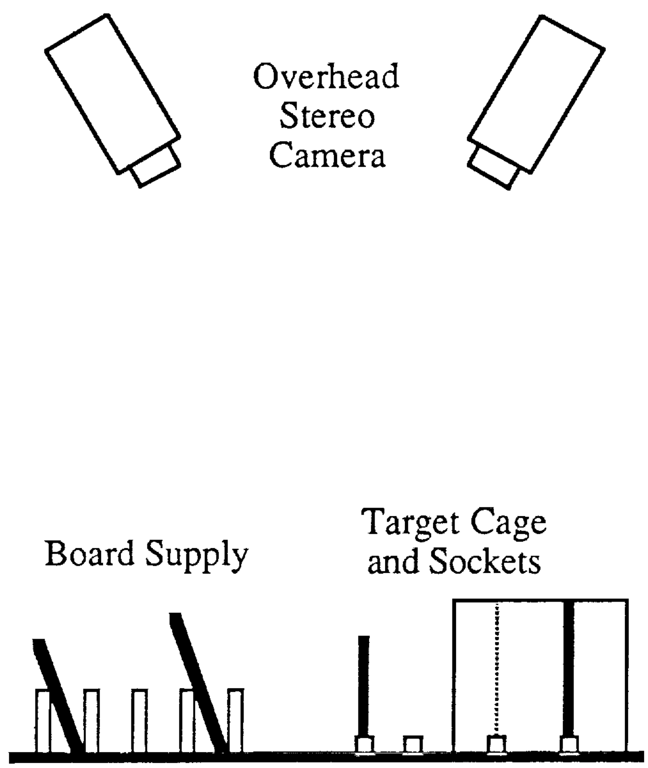

Figure 3. Layout for vision-aided insertion experiment. Overhead stereo cameras view the board supply rack on the left and the target cage and sockets on the right. Two sizes of boards are shown.

developed at JPL by Yakimovsky and Cunningham [19, Kwak 20]. The camera geometric calibration device is shown in Figure 4. The 3D vision system is used to find the gross location of objects in the workcell. The second sensor, a fingertip lightbeam sensor, complements the vision system by providing more accurate position information as previously described. The details of the fingers are shown in Figure 5; note the location-support notch. The third sensor, a wrist-mounted 6D force-torque sensor, monitors the insertion process. The location specialist performs both coarse location and location refinement functions as described in the following two sub-sections.

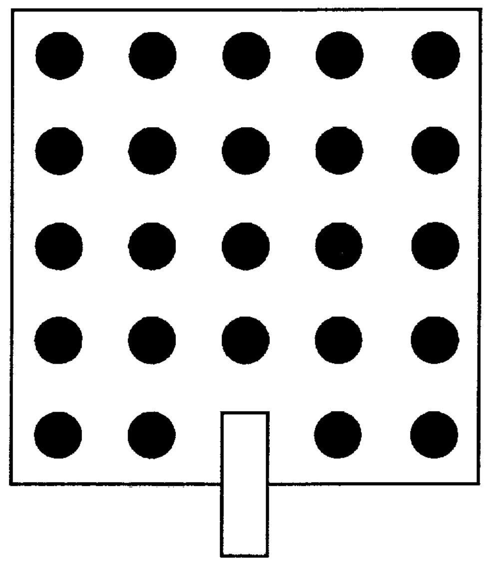

Figure 4. Calibration device: Twenty four black discs on a square grid mounted on an aluminum plate. The position of a finger of the gripper is shown at the bottom center.

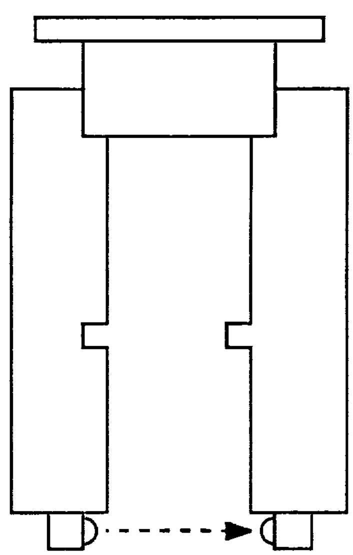

Figure 5. Details of the fingers showing the fingertip light beam sensor. Note the notch used during insertion to locate and support the top of the board.

Coarse Location of Workspace Objects

The printed circuit boards are placed in the robot workcell in a fixture called the board supply rack. The boards are to be inserted in the target cage into guides called the insertion slots. The task starts by taking a picture of the workcell with each camera. In the workcell, the nominal location of the printed circuit boards and the insertion slots is known *a priori*. Thus, in each image, separate windows are defined around the nominal locations of the printed circuit boards and the insertion slots. Confining all image processing to these windows saves time. The windows are sized large enough to accommodate the expected variations in the pose of the supply rack, the boards in the rack, and the insertion slot.

Binary images are created by thresholding each image. For each window, every blob is labelled and moments computed for it. The moment information is used to find a good grasping location on the printed circuit boards as explained next. The boards are approximately vertical and it is desired to grasp them at the midpoint of the top edge. Since the cameras are not looking directly down over the boards, the resulting image of a rectangular board is a parallelogram which corresponds to a 2D projection of the board on the camera image plane. The long edges of the parallelogram correspond to the top and bottom edges of the printed circuit board. First order moments are used to find the centroid of this parallelogram to locate a point in the center of the board.

Since the cameras can be in an arbitrary position relative to the board, the top edge of the parallelogram in the image does not necessarily correspond to the top edge of the board. Thus to determine which edge of the parallelogram represents the top edge of the board, a ray is projected from the camera lens center through the centroid onto an XY-plane, the work surface. If the Y-component of the projection is negative, then the camera is located such that it can be inferred that the top edge of the parallelogram corresponds to the top edge of the board. If the Y-component is positive, then the bottom edge of the parallelogram corresponds to the top edge of the printed circuit board. The binary image is scanned from the centroid towards the top edge of the board to determine the image coordinates of the grasping location on the board. Using the parameters from the camera geometric calibration model, the image coordinates of the grasping location are transformed to the robot coordinates. (A similar approach is used to find the robot coordinates of the insertion slots; the only difference is that the guide height is known *a priori*.) The angular rotation of the boards and the insertion slots in the image is determined using information available from second order moments. The geometric calibration model is used to transform the orientation to the robot coordinates. The overhead 3D vision system has limited resolution and provides positions with about 1 mm uncertainty in the XY-plane and 5 mm in the Z-direction. Due to these limitations, the vision measured coordinates are treated as only first estimates.

Refinement of PC Board Location

Initially, the robot is directed by the insertion task supervisor to move the gripper above the grasping location calculated by the 3D vision system. Then the gripper is moved straight down in small steps monitoring the fingertip lightbeam sensor. When the lightbeam is broken by the top edge of the board, an accurate value for the Z-coordinate of the top edge of the board is obtained. The fingertip lightbeam sensor is also used to find the exact center of this edge by moving the gripper along the length of the board until it finds one edge. This process is repeated to find the other edge of the board.

Insertion of PC Boards

With the X-, Y-, and Z-coordinates of the grasping location specified, the gripper is then moved to that position and the fingers closed. The printed circuit board is picked up by the robot and moved to a position above the insertion slot. The printed circuit board is lowered to within a few centimeters above the top of the slot guides.

At this point, the insertion specialist is invoked and the force-torque sensor zeroed. The fuzzy controller takes over the task of placing the board into the insertion slot guides and then inserting it in the socket. The fuzzy controller returns a vector which consists of six components, each corresponding to the changes to be made in the pose of the gripper. As long as all the components of this vector are below a threshold, the gripper is moved downward (in the negative Z-direction) in small steps to introduce the board into the guides. Otherwise, the gripper is moved to the new pose which is obtained by adding the vector calculated by the fuzzy controller to its current pose values. This procedure is repeated until the board is well into the guides. This procedure is terminated when guide introduction is confirmed by a test motion. This motion consists of twisting the board first clockwise and then counter-clockwise while monitoring the Z-torque level.

Once the board is in the guides, the board is moved in the negative Z-direction in larger steps until the board is close to the height of the socket. The weighting of the vector returned from the fuzzy controller is reduced to account for the fact that the board in in the guides. This is done by using a second set of fuzzy rules written for finer motion. The step size is reduced again during the seating process. At this point the Z-force is monitored to assure the board is seated in the socket without damaging it. Once the board has been inserted, the gripper is opened and moved up vertically to clear the height of the guides. The robot is then directed to pick up the next board and repeat the entire process.

IV. USE OF FUZZY LOGIC

A strategy which is based on fuzzy set theory is used to interpret the forces and torques generated during the printed circuit board insertion process. Deriving a mathematical model to describe an assembly task, like the one described here, is quite cumbersome. If such a model were to be developed, it would be specific to the details of the particular task. An example of a method using a mathematical model for a peg-in-hole problem is presented in Goldenberg and Bazerghi [21]. Instead of using a mathematical model which uses absolute, numerical quantities, however, the fuzzy approach uses approximate relationships. In the real world of robotic assembly, the goals, the constraints and the consequences of the robot actions are not precisely known and, therefore, cannot be modelled exactly. Thus, decisions have to be made using an inference mechanism that can handle uncertain and imprecise knowledge. According to Zadeh [Yager *et al.*, 22], if the gap between human intelligence and machine intelligence is to be narrowed, machines should acquire the ability to manipulate fuzzy concepts and to respond to fuzzy instructions. The use of fuzzy logic which is used for approximate reasoning about insertion tasks is presented next.

Fuzzy Logic and Fuzzy Controllers

Control systems are used to maintain or achieve some desired state of the physical system they control. This is accomplished by monitoring some or all of the state variables of the system and providing appropriate control actions. The design and synthesis of conventional controllers is based on a mathematical model of the plant. Where precise mathematical models are hard to build, human operators are often used as an integral part of the control process. With advances in the area of fuzzy logic and linguistic reasoning, fuzzy controllers are being used to replace human operators as a part of the control process. These controllers use strategies expressed as linguistic statements that resemble human decision making. Holmblad and Ostergaard [23] describe the application of fuzzy logic to the computer control of a rotary cement kiln. They conclude that fuzzy logic is a practical and realistic alternative to traditional means of implementing control strategies based on mathematical models. Fuzzy logic makes reasoning in the real world possible by providing the ability to deal with a continuous range of values rather than just true or false. Elements in fuzzy sets may belong only partially to a set, in contrast to traditional set theory where elements either belong to a set or not [24].

Reasoning about the Task

When an assembly task is performed by a human, the reasoning is often of the form:

IF <sensed condition> THEN <control action> .

Depending upon the parts being assembled, the sensed conditions could be different. In the case of inserting a board into a cage, the sensed conditions could be of the form: "The board is not completely aligned with both guides," or "The board is not being pushed in vertically." The information about the alignment of the board could be obtained visually. The information about the direction of application of the pushing force could be obtained either visually or through contact sensing. The control actions, likewise, could be of the form "Reorient the board slightly to bring it in line with the guides" or "Change the direction of application of the force a little to eliminate the possibility of jamming."

Robot Task Reasoning

When a robot performs the task of a printed circuit board insertion, sensors are needed to obtain the information regarding the process. In this experiment, force-torque information is used to help the robot insert a printed circuit board into a socket whose location is determined using the overhead 3D camera system. The reasoning involved in the robotic insertion task is of the IF-THEN form cited above. The sensed conditions involve terms related to the changes in the forces and torques observed during the process. Typical sensed conditions are of the form: "The X-torque is positive big," or "The Y-torque is negative small," and so forth. The logic value of a condition in ordinary binary logic is restricted to *False* or *True* (0 or 1) whereas in fuzzy logic, the logic value is a measure of the fulfillment of the condition and takes on some value in the interval [0,1]. Fuzzy logic is used to express each of the terms by a unique fuzzy membership function and thus establish a value in the interval [0,1] for a given condition.

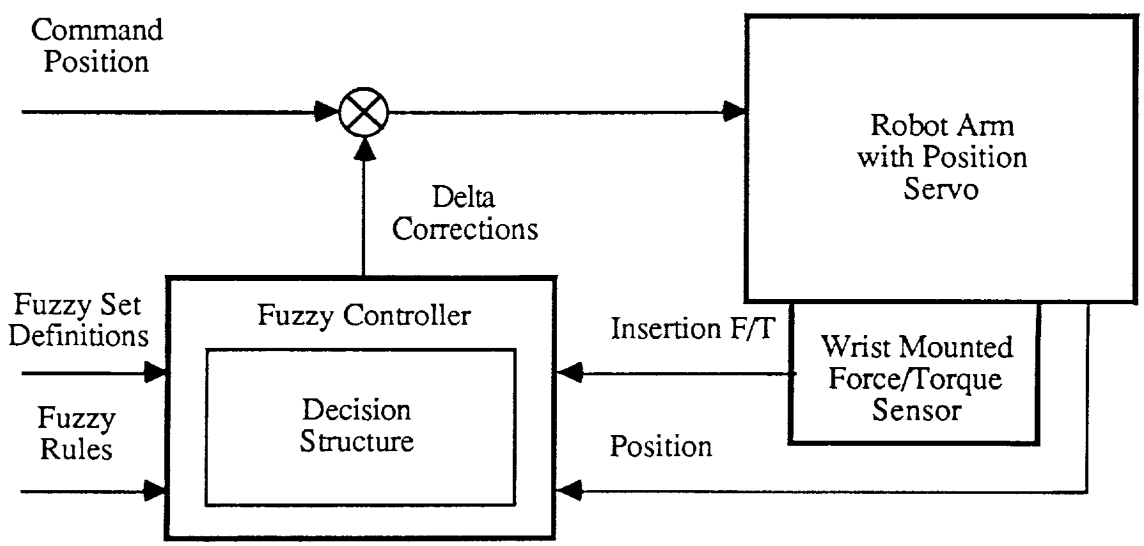

Figure 6. Fuzzy controller block diagram.

Fuzzy Control System

Figure 6 shows a block diagram of the fuzzy control system. The forces and torques read from the sensor form the input to the fuzzy controller. The sensor data is scaled such that the minimum value is -100 units and the maximum value 100. Scaling factors are determined from signatures obtained during trial insertions. All sensor readings are mapped into the [-100, 100] interval, the universe of discourse over which the relevant fuzzy sets are defined. Figure 7 shows the fuzzy sets defined for this insertion experiment.

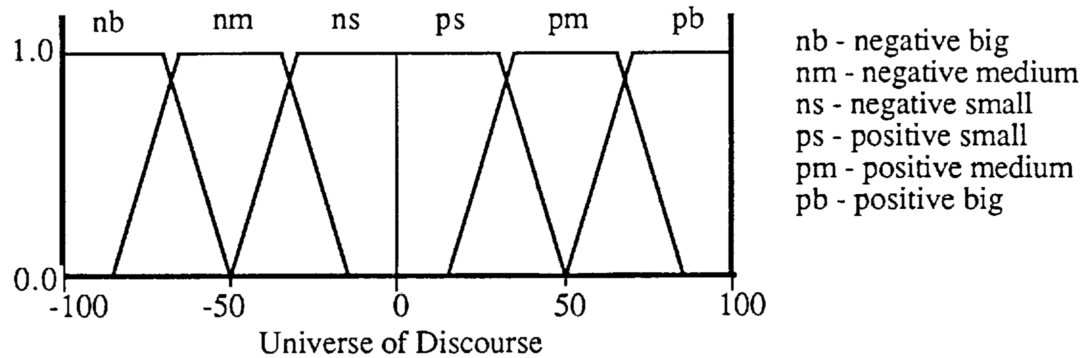

Figure 7. Universe of discourse for the fuzzy sets used in the board insertion experiment.

Fuzzy control rules are used to produce fuzzy sets as output. These sets are defined on the universe of possible control actions, which in this case are incremental changes in the pose of the gripper. The fuzzy control rules are evaluated by means of the compositional rule of inference. This rule is a generalization of the traditional *modus ponens* rule of logical inference. Based on the position of the board in the slot, different sets of rules come into play as previously mentioned. A crisp control action is produced from such fuzzy output sets through the use of the "mean of maxima" scheme. In this scheme, if the output set has a single maxima, then that value is used for the control action. In case several maxima occur in the output set, then the control action is the mean value of these maxima.

The forces and torques generated during a robotic assembly task reflect the status of the process, for example, jamming, misalignment, seating, etc. These forces and torques serve as characterizing features of the process. Using statistical classification techniques, Fuller [25] used such features to classify result of an assembly process as either acceptable or unacceptable. Here, the force and torque features derived from the signatures are used to form a basis for the development of the fuzzy rules. These rules are used to provide real-time corrective measures to accomplish the insertion task. The 6D force-torque signatures of an assembly process can be obtained by recording the forces and torques as the assembly proceeds. For a typical "board into the slot" insertion, the signatures are parameterized with respect to the position along the insertion path. In this case, the Z-position of the board in the guides is used. These signatures are affected by the vibrations of the robot, and have a component that is related to the motion of the robot. Figure 8 shows typical signatures for the robot going through the insertion motion *without* a board in the gripper. The exact values of the forces and torques generated are not necessarily the same for two successive insertions of the same board into the same slot. It can be assumed, however, that there are basic features and trends in the force-torque signature which are common to successful insertions. The basic features may be the peaks and valleys in the signatures. With some uncertainty in the environment, it is difficult to classify these features exactly and thus recognize the actual situation at hand. It is almost impossible to take into account all the possibilities that can arise during an assembly insertion task and store them. Hence, the fuzzy sets are used to characterize the features of signatures. In this way, the fuzzy controller is able to cope with uncertainties and to interpret successfully insertion signatures.

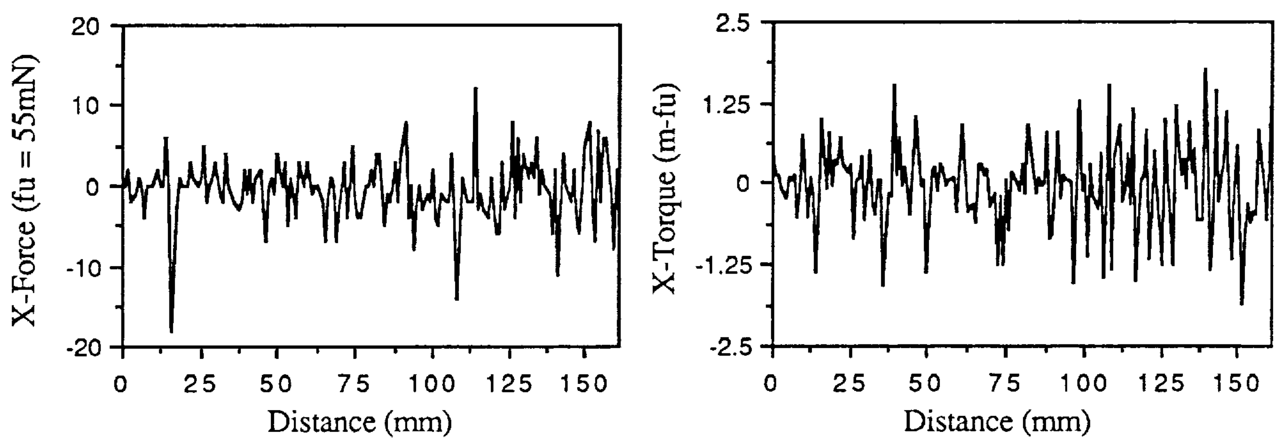

Figure 8. Typical force-torque signatures obtained by performing the board insertion motion *without* a board in the gripper. Note, the range of sensor measurements.

A number of heuristics capturing the fuzzy reasoning process are derived by looking at the geometry of the board insertion problem. Each heuristic is represented as a fuzzy condition-action pair. The condition half tests to see whether the rule is applicable to the situation at hand. The action half consists of a list of actions to be performed if the rule is applicable. The fourteen rules actually used in the insertion experiment are enumerated in the Appendix.

V. FUZZY CONTROLLER EXPERIMENTAL RESULTS

In this section, the experimental results are presented for the performance of an "insertion specialist" which uses the fuzzy controller described previously. The PC board is located using a "location specialist." This information is fed to the robot controller and the gripper is moved from the starting position to a position above the desired board. Since the overhead 3D vision system provides positions with about 1 mm uncertainty in the XY-plane and 5 mm in the Z-direction, the fingertip lightbeam sensor in the finger tips is used to determine the location of the edges of the board more precisely. The pose of the insertion slots are also determined using the vision system.

Next, the board is picked up at the center of its top edge and the arm positioned above the slot where the board is to be inserted. Finally the board is inserted into the guides using the fuzzy controller with feedback from the wrist force-torque sensor. The fuzzy rules are based on the force-torque signatures obtained from prior experiments. Figure 9 shows two of the signatures for a perfect insertion of a board. The increase in the Z-force indicates the seating of the board into the socket. Also, the X-torque shows an increase in magnitude as the board is lowered into the guides because of friction and deviations straight-line motion when the robot is commanded to move in cartesian coordinates.

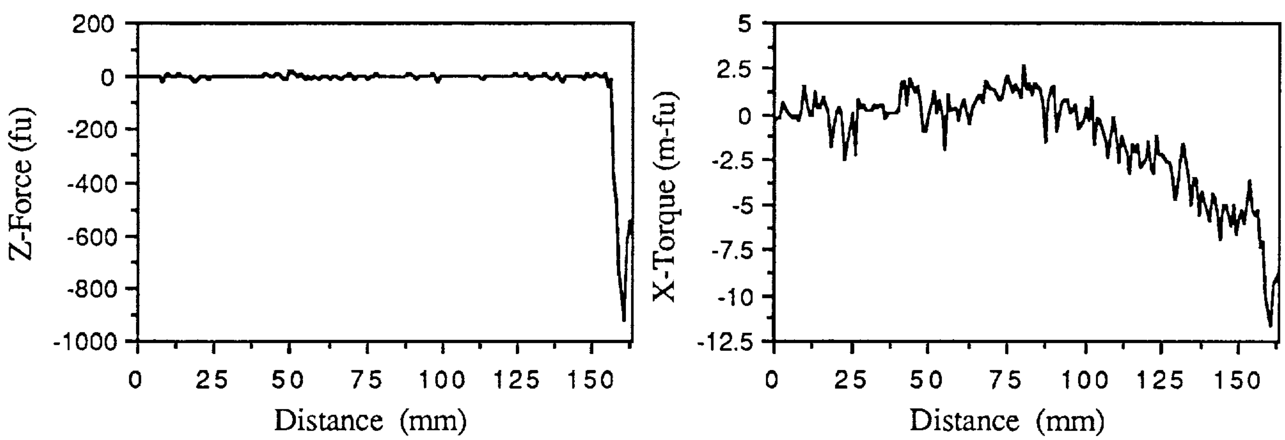

Figure 9. Typical force-torque signatures obtained by performing a perfect board insertion. Note change in scale from Figure 8.

A simple problem that might be faced by an insertion specialist is the near-miss situation shown in Figure 10. The following "common sense" ideas are useful to assure the successful inserting of a board into the guides and the seating of the board in the socket.

1. A medium change in the Z-force and large changes in the X- and Y-torques as the board is lowered indicate that one of the corners of the board is caught on the side of the guide.
2. No appreciable changes in the forces and torques as the board is lowered into the guides indicate that the insertion is proceeding normally.
3. A large change in the Z-force after the gripper has moved approximately the height of the board indicates that the board is being seated into the socket.

A typical rule is shown here written in C.

Rule:	Condition	min = *findmin*(nb, mapxte, pb, mapyte)
	Action	*truncset* (nb, min, tempset)
		maxfn(outset, tempset).

The gist of the rule is that if the scaled value of the X-torque *(mapxte)* is negative big *(nb)* and the scaled value of the Y-torque *(mapyte)* is positive big *(pb)* then the output, *(outset)* should be negative big *(nb)*. *Findmin* examines the fuzzy set *nb* at the point *mapxte* and the fuzzy set *pb* at *mapyte*, and returns the minimum of the two. Then the minimum value is used to truncate the fuzzy set *nb* and create *tempset*, a temporary set. *Maxfn* is used to accumulate the effect of the rules that influence that particular output. It takes the maximum of the two sets *outset* and *tempset* and stores it in *outset*. In this case the output variable is a change in the X-position of the robot arm. This is represented by Delta-X which is obtained by defuzzifying the resulting set *outset* using the mean of maxima scheme.

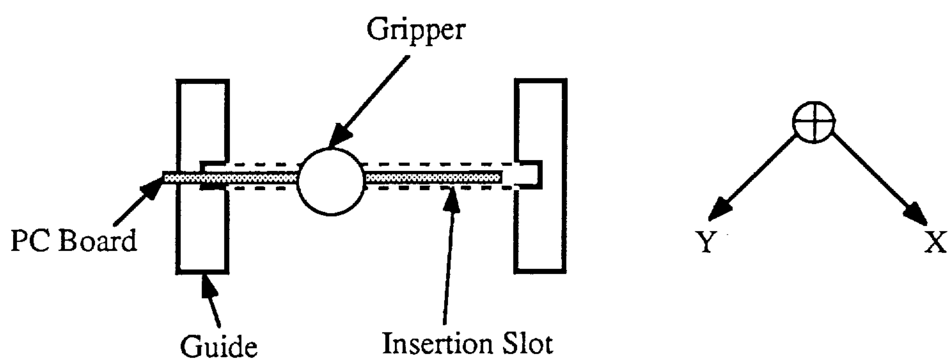

Figure 10. Typical near-miss situation to be handled by the insert board specialist. The orientation of the wrist force-torque sensor coordinate system is indicated.

Figure 11 shows the results of a successful insertion process. The left hand column of graphs shows the measured X- and Z-torques and the Z-force for a typical near-miss insertion. The right hand column shows the incremental modifications to the X- and Y-positions of the gripper and its rotation about the Z-axis commanded by the fuzzy controller. The abscissa for these graphs is the control iteration number; that is, the step where a fuzzy decision is made.

The following control strategy is employed: If the Delta-X, Delta-Y, and the Delta-O are each below its threshold, the board is moved in a fixed increment towards the socket. If any reading is above its threshold, corrective action is taken instead. As can be seen in these graphs, the near-miss situation described in Figure 10 is encountered between control iterations 12-16. The Delta-X and Delta-Y graphs show the corrective measures taken. The change in the rotation as shown by the Delta-O graph relieves the torques by aligning the board. The Z-torque graph illustrates the information gathering process that verifies that the board is in the guides. After control iteration 60, Delta-O outputs are suppressed since the board is well in the guide; this results in a cumulative build-up in Z-torque until the board is released. The seating of the board in the socket is indicated by the sudden increase in the Z-force.

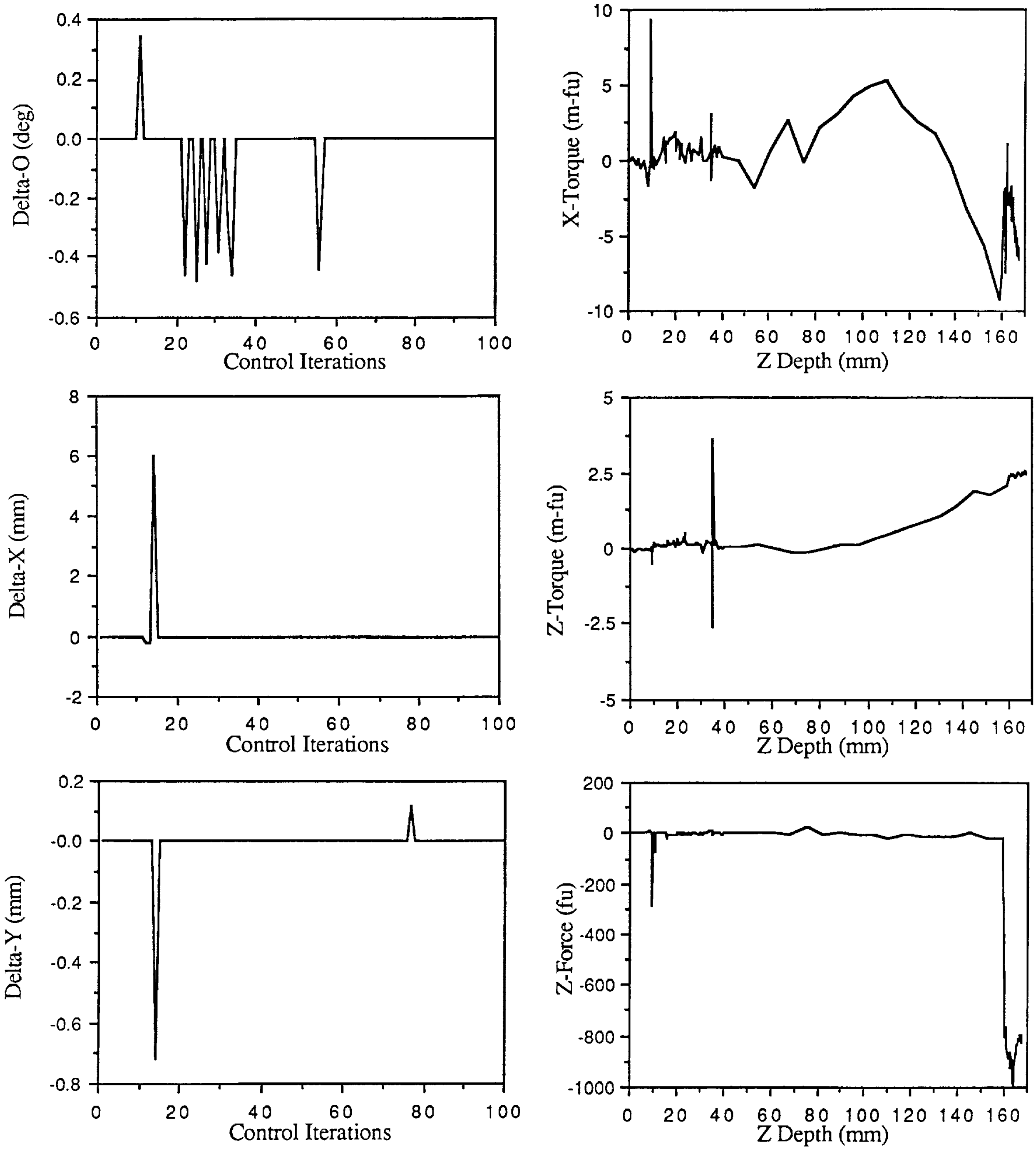

Figure 11. Results of a successful insertion process in the presence of a near-miss situation. See text for discussion.

VI. CONCLUSION

The successful completion of many robotic assembly tasks is hindered by the presence of uncertainties in the environment. These uncertainties may be caused by deviations in part positioning or variations in part dimensions. For two robot systems equipped with multiple sensors, an integrated sensing approach which addresses uncertainties is presented. Two robotic assembly systems are presented which integrate information from different sensors into the insertion task sequence of the robot. The target tasks involve the location and insertion of printed circuit boards into board cages. In the target task, only the nominal position of the PC boards and the insertion slots is known. In both instances, intelligent behavior is accomplished by coupling the insertion task execution sequence with information derived from different sensors. To test some of the sensing concepts, two plausible approaches are explored. One approach examines blind system sensing strategies; the other examines vision sensing in conjunction with fuzzy reasoning. These explorations represent the first steps which lead toward the development of integrated sensing skills to perform generic activities such as *insert* and *locate*. Location and insertion specialists and their activities are described for each experimental approach. For the blind insertion experiment, downward- and sideward-directed proximity sensors, a fingertip infrared lightbeam sensor, and a 4D platform force-torque sensor are used. The blind insertion system employs a search with proximity sensors to locate objects in the work environment. The proximity is used to calibrate the robot to the workspace, and to locate the supply of printed circuit boards and the destination insertion slots. The fingertip lightbeam sensor is used to refine the supply and destination cage location information to the precision required for a successful insertion. The vision-aided insertion system uses a 3D vision system to calibrate the robot to the workspace and to determine the pose of the boards and the insertion slots. It also determines a proper grasping location on the board with the help of the fingertip sensor. A 6D force-torque sensor is used to measure the forces and torques monitored during the insertion process.

A method to apply fuzzy logic techniques to describe relationships between the assembly objects and the data from the sensor is presented. Since the fuzzy controller uses approximate relationships instead of using detailed mathematical models of the insertion process, it is able to handle uncertainties encountered during the actual insertion task. The fuzzy controller can successfully insert PC boards into target insertion guides and sockets as the graphs for a typical near-miss situation demonstrate. This approach to addressing the uncertainties encountered in an assembly task is successful. Pragmatically, the modeling and controller assumptions made in the application of fuzzy set theory to the board insertion domain are validated.

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APPENDIX

Rule Set for the Fuzzy Controller

Rules 1 through 6 use X- and Y-torques to produce Delta-X.

Rule 1:	Condition	min = *findmin*(nb, mapxte, pb, mapyte)
	Action	*truncset* (nb, min, tempset1)
		maxfn(outset1, tempset1).
Rule 2:	Condition	min = *findmin*(nm, mapxte, pm, mapyte)
	Action	*truncset* (nm, min, tempset1)
		maxfn(outset1, tempset1).
Rule 3:	Condition	min = *findmin*(ns mapxte, ps, mapyte)
	Action	*truncset* (ns, min, tempset1)
		maxfn(outset1, tempset1).
Rule 4:	Condition	min = *findmin*(ps, mapxte, ns, mapyte)
	Action	*truncset* (ps, min, tempset1)
		maxfn(outset1, tempset1).
Rule 5:	Condition	min = *findmin*(pm, mapxte, nm, mapyte)
	Action	*truncset* (pm, min, tempset1)
		maxfn(outset1, tempset1).
Rule 6:	Condition	min = *findmin*(pb, mapxte, nb, mapyte)
	Action	*truncset* (pb, min, tempset1)
		maxfn(outset1, tempset1).

Rules 7 through 10 use Z-torque to produce Delta-O.

Rule 7:	Condition	min = *findmin*(pm, mapzte, pm, mapzte)
	Action	*truncset* (ns, min, tempset2)
		maxfn(outset2, tempset2).
Rule 8:	Condition	min = *findmin*(nm, mapzte, nm, mapzte)
	Action	*truncset* (ps, min, tempset2)
		maxfn(outset2, tempset2)

Rule 9:	Condition	min = *findmin*(pb, mapzte, pb, mapzte)
	Action	*truncset* (ns, min, tempset2)
		maxfn(outset2, tempset2).
Rule 10:	Condition	min = *findmin*(nb, mapzte, nb, mapzte)
	Action	*truncset* (ps, min, tempset2)
		maxfn(outset2, tempset2).

Rules 11 and 12 use X- and Y-force to produce Delta-Y.

Rule 11:	Condition	min = *findmin*(pb, mapxfe, pb, mapyfe)
	Action	*truncset* (ps, min, tempset3)
		maxfn(outset3, tempset3).
Rule 12:	Condition	min = *findmin*(nb, mapxfe, nb, mapyfe)
	Action	*truncset* (ns, min, tempset3)
		maxfn(outset3, tempset3).

Rules 13 and 14 use X- and Y-force to produce Delta-X.

Rule 13:	Condition	min = *findmin*(pb, mapxfe, pb, mapyfe)
	Action	*truncset* (ns, min, tempset1)
		maxfn(outset1, tempset1).
Rule 14:	Condition	min = *findmin*(nb, mapxfe, nb, mapyfe)
	Action	*truncset* (ps, min, tempset1)
		maxfn(outset1, tempset1).

REFERENCES

1. J.F. Engelberger, *Robotics in Practice*, amacom division of American Management Association, 1980.
2. S. Mujtaba and R. Goldman, "AL user's manual," 3rd ed., Report no. STAN-CS-81-889, Stanford Univ. (1981).
3. J.C. Latombe and E. Mazer, "LM: A high-level programming language for controlling manipulators," 11th Int. Symp. on Industrial Robots, Tokyo, Japan, 683-690 (1981).
4. R.H. Taylor, P.D. Summers, and J.M. Meyer, "AML: A manufacturing language," *Int. J.of Robotics Research,* **1**(3), 19-41 (1982).
5. R.A. Brooks, "Symbolic error analysis and robot planning," *Int. J. of Robotics Research*, **1**(4), 29-68 (1982).
6. B. Dufay and J.C. Latombe, "An approach to automatic robot programming based on inductive learning," *Int. J. of Robotics Research*, **3**(4), 3-20 (1984).

7. M.R. Cutkosky and P.K. Wright, "Position sensing wrists for industrial manipulators," Int. Symp. on Industrial Robots, Paris, France, 427-438 (1982).

8. J.L. Nevins, T.L. Defazio, E.J. Consales, J.B. Ford, R.E. Gustavson, D. Killoran, J.F. Padavano, R.C. Roderick, D.S. Seltzer, C.C. Selvage, S.N. Simunovic and D.E. Whitney, "Exploratory research in industrial assembly part mating," The Charles Stark Draper Laboratory Inc., Cambridge, MA, Seventh progress report for the National Science Foundation (1980).

9. J.L. Nevins and D.E. Whitney, "Research on Advanced Automation," *Computer*, Dec. 1977, 24-39.

10. L. Basañez, R.B. Kelley, M.C. Moed, C. Torras, "A Least-Commitment Approach to Intelligent Robotic Assembly," IEEE Int. Conf. on Robotics and Automation, Philadelphia, PA, 1318-1319 (1988).

11. R.B. Kelley and M.C. Moed, "Knowledge-Based Robotic Assembly Systems," *Advances in Automation and Robotics*, G.N.Saridis, ed., **2**, Jai Press Inc, 1989.

12. R.B. Kelley, S. Bonner, "Understanding, Uncertainty, and Robot Task Execution," 1st IFAC Symposium on Robot Control (SYROCO '85), Barcelona, 331-335 (1985).

13. R.B. Kelley, "Vertical Integration for Robot Assembly Cells," IEEE Int. Conf. on Robotics and Automation, San Francisco, CA, 585-590 (1986).

14. M.C. Moed, R.B. Kelley, "The Design of an Assembly Cell Task Supervisor." IEEE Int. Conf. on Robotics and Automation, Philadelphia, PA, 652-653 (1987).

15. M.C. Moed, R.B. Kelley, "An Expert Supervisor for a Robotic Work Cell," SPIE Conf. on Intelligent Robots and Computer Vision, Cambridge, MA, 496-501 (1987).

16. D. Sood, M. Repko, M. Moed and R.B. Kelley, "A Fuzzy Approach to the Interpretation of Robot Assembly Forces," SPIE Conf. on Intelligent Robots and Computer Vision, Cambridge, MA, 426-433 (1988).

17. D. Sood, M. Repko and R.B. Kelley, "Using Multiple Sensors for Printed Circuit Board Insertion," NASA Space Telerobotics Conf., Pasadena, CA (in press) (1989).

18. D. Sood, M. Repko and R.B. Kelley, "Design and Implementation of a Multi-Sensor Robot System for Printed Circuit Board Insertion," Int. Conf. on Robotics and Automation, Scottsdale, AZ, 377-382 (1989).

19. Y. Yakimovsky and R. Cunningham, "A system for extracting three-dimensional measurements from a stereo pair of TV cameras," *Computer Graphics and Image Processing*, **7**, 195-210 (1978).

20. W.I. Kwak, "Design, analysis, and application of a 3-D vision system in computer integrated manufacturing," Ph.D dissertation, ECSE Dept., Rensselaer Polytechnic Institute, Troy, New York (1988).

21. A.A. Goldenberg and A. Bazerghi, "A preview approach to force control of robot manipulators," *Mechanism and Machine Theory*, **20**(5), 449-464 (1985).
22. R.R. Yager, S. Ovchinnikov, R.M. Tong, and H.T. Nguyen, *Fuzzy Sets And Applications: Selected Papers by L.A. Zadeh*, John Wiley & Sons, 1987.
23. L.P. Holmblad and J.J. Ostergaard, "Control of a cement kiln by fuzzy logic," *Fuzzy Information and Decision Processes*, M.M. Gupta and E. Sanchez, eds., North Holland Publishing Co., 1982, 389-400.
24. G.J. Klir and T.A. Folger, *Fuzzy Sets, Uncertainty and Information*, Prentice Hall, Englewood Cliffs, NJ, 1988.
25. D.M. Fuller, "Signature analysis of robotic assembly forces - A flexible sensor system," Xerox Corporation Report, Webster, NY (1985).